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Path Planning Method in Taigu County Based on the Hybrid Ant Colony Optimization-Genetic Algorithm in the Context of COVID-19

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Abstract. During the period of COVID-19, there is a mixture of areas that are susceptible to COVID-19 infection and areas that are not susceptible to COVID-19 infection in cities. Blind wandering is often accompanied by the risk of infection. Hence, in order to improve the safety of people's travel, this paper uses the hybrid Ant Colony Optimization-Genetic Algorithm (ACO-GA) to plan the central path of Taigu County. The volatilization coefficient of pheromone in Ant Colony Optimization (ACO) is changed dynamically. Pheromones in high-risk areas that are susceptible to epidemic infection are more volatile, while pheromones in low-risk areas that are less suscep-tible to epidemic infection are less volatile. Adjust the selection of "gene" mutation in Genetic Algorithm (GA). Vulner-able areas should be closed off to cut off the source of infection. As long as the shortest route which is of lower risk is formulated, people should stay away from high-risk areas that are susceptible to infection as much as possible to reduce the spread of COVID-19 and ensure the safety of people's lives. The path under the influence of the COVID-19 is predicted and analyzed in the form of a simulation. The experimental results show that the algorithm can help to effectively avoid areas susceptible to the COVID-19 and reduce the risk of people getting sick.

Keywords: path planning, ACO algorithm, GA

1 Introduction

In December 2019, the large-scale outbreak of COVID-19 caused many casualties and economic losses [1]. As of August 1, 2022, the cumulative number of confirmed COVID-19 cases worldwide has exceeded 577 million, and the cumulative number of COVID-19 deaths worldwide has exceeded 6.4 million [2]. Since March 2022, the Omicron strain has been mutating continuously, and the increase of Omicron cases in infectivity and prevalence has led to a surge in the number of infected patients [3]. Most countries have ended all COVID-19 restrictions and implemented a new strategy of "living with COVID-19" [4]. The dynamic zero-case strategy [5] implemented by China effectively has controlled the development of the epidemic. Intervention measures such as border isolation and community isolation to keep people away from densely populated areas are effective strategies to prevent the exponential growth of regional epidemics [6-7]. During COVID-19, residents are afraid of being infected and at risk of becoming infected when traveling. In the process of travel, if the navigation software can provide the travel path based on the mechanism of avoiding medium-high risk areas and some crowded places, then pedestrians and vehicles can reasonably plan the route and reduce the possibility of being infected by the virus. Taking Taigu County, Jinzhong City, Shanxi Province, China as an example, the problem of path planning under the condition of dynamic zero-case control is studied, and an improved algorithm for fast path planning in small and medium-sized cities is proposed.

In order to reduce person-to-person contact and reduce the risk of cross infection, route planning is particularly important during the epidemic. A contactless distribution route optimization algorithm [8] based on the improved Ant Colony Optimization (ACO) is proposed by Wu et al., which can adjust the route in real time according to the traffic situation and improve the efficiency of distribution. In order to solve the route planning problem of emergency vehicle scheduling and transportation of medical waste before and after public health events [9], a hybrid optimization algorithm based on the combination of immune algorithm, ACO and tabu search algorithm

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is proposed by Liu et al. A hybrid particle swarm optimization algorithm [10] based on genetic improvement set is proposed by Zhang et al., which can solve the problem of multi-station vehicle routing cooperative persistent distribution of swarm robots based on mixed integer linear programming (MILP). According to the requirements of isolation of high-risk individuals under large-scale epidemics, a hybrid algorithm based on meta-heuristic of water wave optimization and neighborhood search [11] is proposed by Zhang et al., which can solve the route problem of isolated vehicles under epidemics. For the fresh food distribution problem under the epidemic situation, Jin et al. adopted the Max-Min ACO to solve the distribution route optimization model constructed [12], and proposed that the application of the hybrid algorithm combining other algorithms and ACO to route optimization would become a future research trend. Therefore, choosing a reasonable and fast path planning algorithm can effectively solve the travel problem under the condition that the road is closed at any time, according to the implementation of various control measures during the epidemic.

The main contributions of this paper are as follows:

1) A hybrid Ant Colony Optimization-Genetic Algorithm (ACO-GA) is proposed which takes the effect of epidemic infection into account. By changing the pheromone volatilization mechanism of the ACO, the vulnerable areas are avoided in the route planning. The Genetic Algorithm (GA) is used to accelerate the convergence of the algorithm, and the areas susceptible to the epidemic infection are also avoided accordingly.

2) A fast path planning scheme suitable for small and medium-sized cities under the condition of dynamic control is provided. The densely populated area of Taigu County is taken as the study area. First, the road vector map in the main urban area is processed by Arcgis. Second, in the grid environment, pheromones are graded according to the extent to which different regions are affected by the epidemic infection. Finally, a hybrid algorithm combining ACO and GA is applied to route selection under the influence of the novel coronavirus epidemic, and a feasible route planning method for people's safe travel is provided.

The rest of the paper is organized as follows: The section 2 introduces the work related to ACO. The section 3 describes the related techniques of ACO and GA. In section 4, a ACO-GA considering the influence of epidemic is proposed. The experimental and analytical part is in section 5. Finally, the paper is summarised in section 6.

2 Related Work

Path Planning is a hot topic in intelligent technology research, which has made breakthroughs and been successfully applied in many fields [13]. Applications in the field of high-tech include automatic planning of unmanned aerial vehicle (UAV) flight paths [14], cruise missiles dodge radar searches [15], and intelligent robot control, etc. [16]. There are also many daily applications, such as path planning based on geographic information system (GIS) [17], urban intelligent traffic dynamic path planning [18], logistics or takeaway delivery [19], and automated guided vehicle (AGV) path planning and scheduling, etc. [20]. So far, there are many kinds of algorithms in the research and development of path planning algorithms [21], ranging from basic Dijkstra algorithm and A* algorithm to various intelligent algorithms, such as simulated annealing algorithm, neural network algorithm, ACO and GA [22]. In recent years, combining path planning algorithm with specific application scenarios is still an important research direction. For example, Miao et al. [23] proposed an improved adaptive ACO to transform path planning into a multi-objective optimization problem by introducing multi-objective performance indicators to realize global comprehensive optimization of robot path planning. In order to solve the path planning problem of UAV under multiple threats in complex environment, particle swarm optimization algorithm based on spherical vector is proposed by Phung et al. [24]. It transforms the path planning into an optimization problem, and finds the minimum value of the cost function by searching the configuration space of the UAV effectively, which is to solve the optimal path. Zhou et al. [25] proposed an advanced swarm optimization algorithm based on Bat algorithm (BA) to improve UAV flight paths in three-dimensional space. By combining standard BA with artificial bee colony algorithm (ABC), ABC is used to improve BA, which solves the shortcoming of poor local search ability of BA. Liu et al. [26] designed a new inertia weight and updating rule of learning factor, which overcomes the disadvantage that traditional particle swarm optimization is easy to fall into local optimality. And it is combined with fuzzy neural network to solve the path planning problem of intelligent driving vehicle. The above studies show that a single optimization algorithm is often unable to effectively solve multi-objective combinatorial optimization problems, so it often needs to be combined with other intelligent optimization algorithms to find the optimal solution.

ACO is often used for path planning, which has strong robustness and the ability to find better solutions. However, it has some disadvantages such as long searching time, slow convergence speed and easy stagnation.

To solve these problems, scholars have proposed two kinds of improvement methods: the first improvement method is to improve parameters such as pheromone heuristic factor, expected heuristic factor and pheromone concentration in the algorithm. For example, the initial parameters of the ACO, pheromone factor α and heuristic function factor β , are used by Tian et al. [27] for combinatorial optimization using particle swarm optimization, which improved the quality of solution and the speed of convergence. A designed S-shaped attenuation function is used to adaptively reduce the influence of heuristic information, and an amplification roulette method with an adjustable growth function to accelerate the convergence of the ACO is proposed by Hou et al. [28]. By adjusting the weight factors of pheromone and heuristic information to improve the updating rules of pheromone in the ACO, Li et al. [29] solved the shortcomings of low search efficiency and easiness to fall into local optimal. The second improvement method is to combine traditional ACO with other intelligent algorithms. For example, in order to improve the local searching ability and convergence speed of the algorithm, a knowledge-based hybrid ACO is proposed by Li et al. [30], which added the bacterial foraging algorithm to the ACO. Combining the heuristic strategies of particle swarm optimization algorithm and ACO, an adaptive hybrid optimization algorithm is proposed by Jiang et al. [31], which has high search efficiency and strong optimization ability. A hybrid method combining ACO and Firefly Algorithm (FA) is proposed by Farisi et al. [32] to obtain better optimization results and convergence time. A hybrid algorithm combining ACO and GA is proposed by Ding et al. [33], which optimized the distribution of the pheromone through GA and improved the search efficiency of the algorithm.

In this paper, the ACO is used to search the road for the irregular blockade and control during the epidemic period. In order to overcome the problem of slow convergence of the ACO in the late stage, the GA is used to search the optimal path twice on the basis of the path searched by the ACO, so that rapid convergence can be achieved in the late stage of algorithm.

3 The ACO-GA Related Technologies

The ACO-GA proposed in this paper needs to process the input map data first, and input the rasterized data formed after processing into the ACO-GA for path planning. This algorithm mainly involves map rasterization technology, the ACO and GA in the process of data preprocessing.

3.1 Data Preprocessing

Use ArcGIS software to import the source data obtained from Penstreetmap. The source data contains layers such as points, places, roads, railways, waterways and buildings. Since the research is mainly to avoid the risky location of the COVID-19 and choose a reasonable path, the three layers: data of points, places and roads are retained, and other layers are deleted.

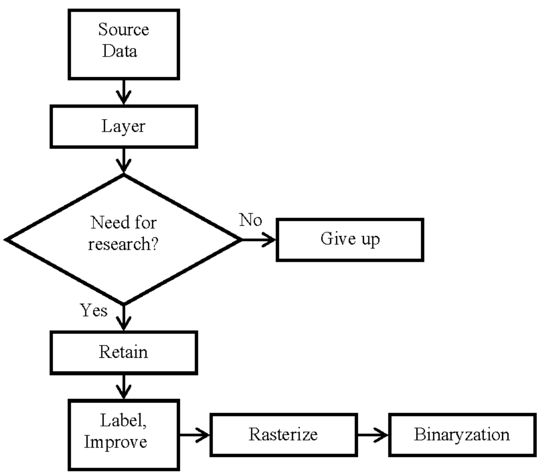


Fig. 1. Flowchart of data preprocessing

Next, the data is improved according to the actual situation. On the basis of checking the topology error of the data and surveying the actual situation, the corresponding attribute fields are set for the road, and the road is marked. At the same time, the duplicate road sections are deleted, and the disconnected road sections are repaired to ensure the integrity of the path and connection. According to research needs, we will mark important locations in the points layer, such as train stations, schools, hospitals, etc. In the places layer, the medium and high risky areas where the COVID-19 occurred are mainly marked.

Then, according to the government's policy on the division of the COVID-19 situation into regions, the key control areas are selected as the research areas. The road map of the selected research area is rasterized to form a raster map. The raster map is then binarized to form a binarized path map, which provides a data basis for subsequent path planning research. The specific data preprocessing process is shown in Fig. 1.

3.2 ACO Algorithm

The Basic Principle of the ACO. The ACO is first proposed by the Italian scholar Marco Dorigo in 1991 [34], which simulated the behavior characteristics of foraging ant groups in nature and is successfully used to solve the Traveling Salesman Problem. In the real environment, ants will release a volatile substance - pheromone on the path of finding objects [35]. Studies have shown that different ants can choose the path with large pheromone with a high probability through the state transition probability based on pheromone intensity. The location with high pheromone concentration can attract more ants, and the amount of information on the optimal path will increase. The amount of information on other paths gradually decays [36]. Finally, under the action of the positive feedback mechanism of pheromone concentration, the entire ant colony could find the optimal path between the nest and the food source. The flowchart in Fig. 2 shows the basic steps of the ACO.

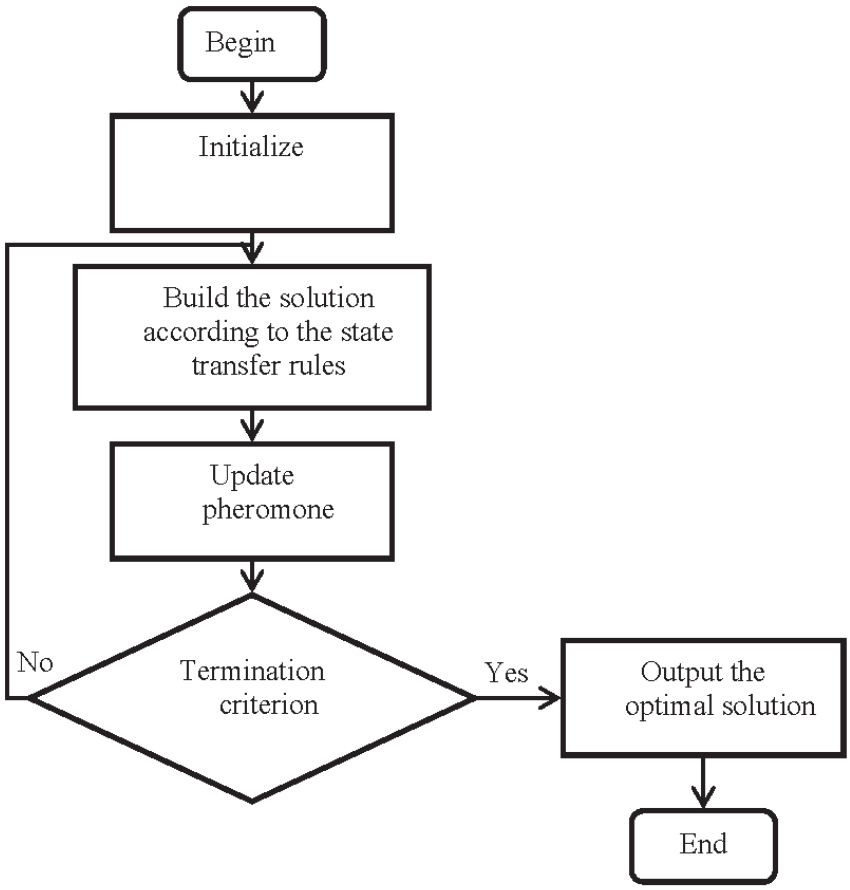


Fig. 2. The flow chart of the ACO

Key Technologies of the ACO.

Status Transfer Rules. At the beginning of the algorithm, the ant randomly selects a node, and then the ant moves a node to another node until all nodes are traversed. Assuming that i is the starting point of the foraging ants, the random travel probability of reaching the foraging end point j is expressed as formulas (1) and (2).

$$P_{ij}^{k}=\begin{cases}\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}{\sum\limits_{j\in \text{allow}_k}\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}}, j\in \text{allow}_k \\ 0, j\notin \text{allow}_k\end{cases}, \tag{1}$$

$$\eta_{ij}(t)=\frac{1}{d_{ij}}. \tag{2}$$

In formula (1), α is established as the pheromone heuristic factor. β represents the expected heuristic factor. τ_{ij} stands for the pheromone concentration of the path (i, j) is the set of all next reachable nodes in the path search. In formula (2), η_{ij} represents the heuristic information. d_{ij} is established as the Euclidean distance between the current node i and the candidate node j. It can be clearly seen from the above two formulas that the road segment with more pheromone and shorter distance is easier to be selected.

Pheromone Volatilization and Renewal. The pheromone left by the ants on the road section will volatilize as the time passes by, so the pheromone on the ant path in each iteration needs to be updated when the algorithm is running. The pheromone update rule is shown in the following formulas (3) and (4).

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\Delta\tau_{ij}(t,t+1), \tag{3}$$

$$\vartriangle\tau_{ij}(t,t+1)=\begin{cases}\dfrac{Q}{L_k}, \textit{The ant with number } k \textit{ passes through the path } (i,j) \textit{ in this iteration} \\ 0, \textit{Other}\end{cases}. \tag{4}$$

In formula (3): ρ represents the pheromone volatilization coefficient, $\rho\in(0,1)$ $\Delta\tau_{ij}(i, j)$ represents the incremental size of the pheromone from node to node j In formula (4) : Q is the pheromone intensity. L_k represents the total length of the path taken by the kth ant in this iteration.

3.3 The GA

The Basic Principles of GA. GA is first proposed by the American professor Holland in 1975 [37]. It is a stochastic global search and optimization method developed by imitating the biological evolution mechanism in nature. By referring to Darwin's theory of evolution and Mendel's theory of heredity, GA searches the space by means of knowledge accumulation, and adaptively controls the search process in solving the optimal value. The solving process of GA is similar to the operation such as crossover and mutation of chromosome genes in biological evolution [38], which enables individuals in the population to evolve, and the new individuals after evolution can better adapt to the environment compared with the old ones. One chromosome in the GA corresponds to a solution, and the quality of the solution is judged by calculating the fitness function.

The optimization idea of GA is to simulate the nonlinear programming problem to be solved as the evolution process of natural organisms [39], and its algorithm flow chart is shown in Fig. 3. The initial population produces the next generation of individuals that better suit the environment through random selection, crossover and mutation operations. And gradually eliminate the individuals with low fitness function value, and retain the individuals with high fitness function value, which makes the population evolution. In this way, individuals with higher fitness function values are obtained through continuous reproduction and evolution from generation to generation, which generates the optimal solution of the target problem function.

Components of GA.

(1) Chromosome coding. By means of coding, the objective function optimization problem is transformed into the searching space problem of GA. Binary coding is commonly used.

(2) Fitness function. It is used to judge the quality of individuals in the population, and it should be designed according to the problem solved, usually with a positive value.

(3) Genetic operator. Selection operators, crossover operators and mutation operators are used to describe the genetic mechanism. Among them, the selection operator is used in the process of survival of the fittest, and the roulette selection method is commonly used to select individuals according to the proportion of fitness function values. Crossover operators are used to expand searching space, increase searching diversity, and generate off-spring with better gene combination. Mutation operators are used for gene mutation to generate new individuals and maintain species diversity.

(4) Termination conditions. The GA achieves the condition of convergence. When the maximum number of iterations is satisfied or the fitness function value of the individual remains in a stable state, the calculation is stopped.

(5) Operation parameters. It mainly includes population size, crossover probability, mutation probability, selection operator, fitness function and maximum number of iterations.

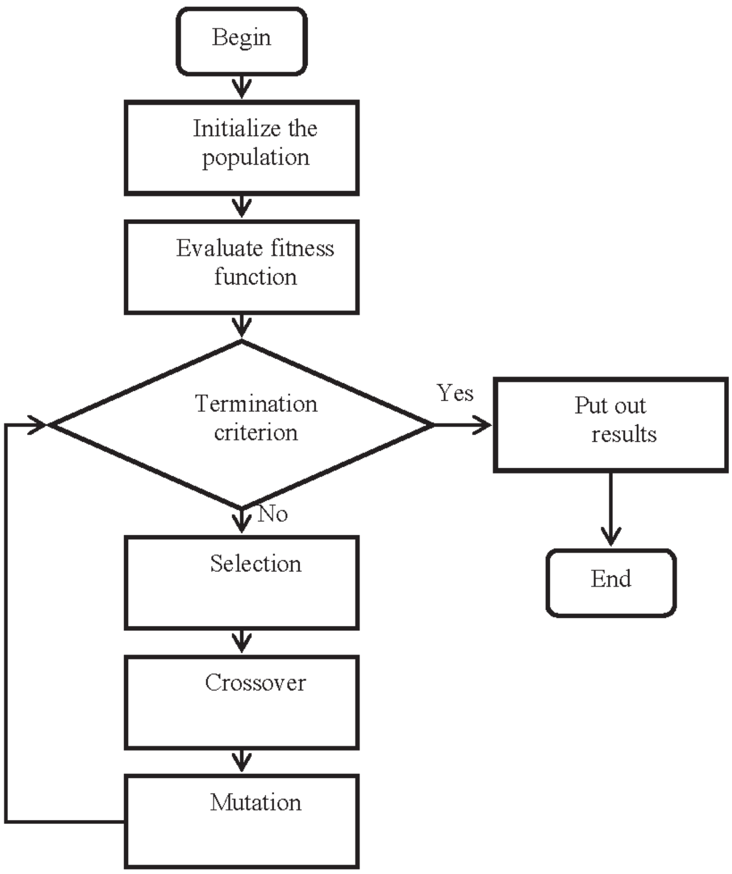


Fig. 3. The flow chart of the GA

3.4 The ACO-GA

ACO simulates the foraging behavior of ant colony. Compared with other heuristic algorithms, it has parallelism, positive feedback, easy implementation and strong robustness. Therefore, the ACO can be easily combined with other algorithms, which is to improve the performance of the algorithm. However, the ACO also has problems such as long searching time, slow convergence speed, and easiness to fall into local optimum.

GA is to search for the optimal solution by simulating the natural evolution process. The algorithm has the characteristics of parallelism, randomness and scalability, which are easy to be combined with other algorithms. However, since there is no feedback information, the searching speed of the algorithm is slow. The GA has a certain dependence on the selection of the initial population, and can be improved in combination with other algorithms. The GA can quickly search all the solutions in the solution space, and has good global searching ability. Therefore, it can overcome the disadvantage that ACO is prone to fall into local optimization.

In this paper, the ACO and GA are combined, which can give a full play to their advantages and make up for their shortcomings. Table 1 shows the pseudo code of the ACO-GA. The ACO-GA first calculates the transfer probability through the ACO, traverses all nodes, updates the pheromone, and calculates the path of each ant and its path length in each iteration. The GA initializes the genetic population according to the path of each ant for each iteration stored by the ACO. The population is updated through selection, crossover and mutation operations, and finally the optimal solution of the algorithm is obtained. The ACO-GA fuses the two heuristic algorithms through the strategy of "the whole first, then the local". It solves the shortcomings of the ACO's easily falling into local optimum and slow iteration speed, and improves the problem of GA's selecting initial population. The ACO-GA has good robustness and scalability.

Table 1. The pseudo-code of the ACO-GA

Algorithm 1. The ACO-GA

```
1: Initialization parameters
2: while i<= the maximum number of iterations   % ACO
3:   Calculate the transfer probability and iterate over all points
4:   Routes sores the path of each ant for each iteration
5:   PL stores the path length of each ant for each iteration
6:   Update pheromone
7: end
8: Generate initial population according to routes  % GA
9: for j=1: evolutionary generation
10:  Selection
11:  Crossover
12:  Mutation
13:  Population update
14:  Update optimal solution  % shortest path
15: end
```

4 The ACO-GA Considering the Influence of COVID-19 Infection

4.1 Epidemic Prevention and Control Measures in Taigu District

In order to ensure people's safety, Taigu District has issued a number of epidemic prevention and control regulations, which encourage people to cancel non-essential gatherings and call on the general public to strictly abide by relevant regulations on epidemic prevention and control. Take good personal protection, wear masks, wash hands frequently and disinfect frequently. Always pay attention to the health code, travel code. If anything becomes abnormal, report it to the community or employer. Taigu District implemented strict control and management on key parts involved in the epidemic. When traveling, people should try to stay away from the severely affected areas, avoid being infected by COVID-19, and move to safe areas.

The specific process of epidemic prevention and control measures in Taigu District is as follows:

First, learn about new cases and confirmed cases in different places based on real-time big data reports on the epidemic on the Internet.

Second, we will delimit high-risk, medium-risk and low-risk areas in each region and implement hierarchical management.

Third, insist that all staff do nucleic acid, and if they are going to enter public places, they should voluntarily show a negative nucleic acid certificate within 3 days.

Fourth, the activity track of new cases should be released, close contacts should be sought, and diagnosis and treatment should be carried out in isolation.

Fifth, establish isolation zones for confirmed cases, trace their source in time, conduct nucleic acid sampling, isolate and control, and maintain real-time monitoring.

Sixth, people should be evacuated from crowded areas to avoid the risk of infection caused by crowd gathering.

Seventh, road and city blocks should be carried out in severely affected areas to avoid the expansion and spread of COVID-19 to the greatest extent.

4.2 Path Selection Considering the Impact of COVID-19 Infection

Under the influence of COVID-19, different regions have made different protective measures according to the degree of susceptibility towards infection. Taigu District identified high-risk, medium-risk and low-risk areas according to the epidemic prevention and control regulations issued. They are marked with black squares on the map to indicate areas susceptible to high risk, as shown in Fig. 4(a). This paper is based on the ACO-GA, and different treatments are adopted according to different regions affected by the COVID-19 infection. First, the map matrix processed by the algorithm is divided into two categories: vulnerable areas and non-infectious areas. Secondly, analyze the ACO and the GA respectively, whether it is affected by the factors which are affected by the COVID-19 area.

The ant colony chooses the path mainly according to the pheromone concentration left on the path. In ACO, the pheromone concentration on the path is affected by the changing of the pheromone evaporation coefficient. The pheromone of the ACO is updated by setting different pheromone evaporation coefficients. The volatilization coefficient of pheromone passing through the area is assigned according to whether the area is affected by epidemic infection. In areas affected by the Covid-19, we have chosen routes as far away from vulnerable areas as possible. Pheromone volatilization coefficient is dynamically adjusted according to the situation of different regions affected by the epidemic. The risk of epidemic transmission is high in susceptible areas. In order to avoid passing through this area, a large pheromone volatilization coefficient should be set to reduce the pheromone concentration along this path. People tend to go to low-risk areas that are less susceptible to infection, and these areas have smaller pheromone volatilization coefficients, which can preserve the concentration of pheromones along the path.

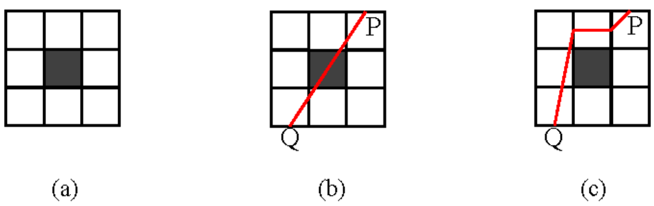


Fig. 4. Schematic diagram of susceptible area identification

Without changing the pheromone volatilization coefficient, the path selection from point P to point Q is shown in Fig. 4(b), which only considers the length of the path distance. The path chosen in this way is likely to pass through high-risk areas susceptible to epidemic infection, which increases the probability of people being infected. The possible path selection from point P to point Q is shown in Fig. 4(c) under the consideration of epidemic risk division. The change of pheromone volatilization coefficient increases the probability of choosing low-risk areas. The selected route, considering the distance, avoids the areas vulnerable to the epidemic as much as possible, and reduces the risk of people being infected by the epidemic to a certain extent. The pseudo-code of the ACO considering the impact of COVID-19 infection is shown in Table 2.

The GA optimizes the ACO based on the global searching to find the path of each ant in each iteration. Under the condition of considering the impact of COVID-19 infection, in order to avoid backtracking and reduce the complexity of the algorithm, the solution space is simplified. Enclosing the areas susceptible to COVID-19 infection on the map matrix can speed up the convergence speed of the GA and improve the local searching ability. Especially when performing mutation operations, it can effectively prevent "genes" from mutating to areas susceptible to COVID-19. As shown in Fig. 5, Fig. 5(a) to Fig. 5(c) respectively represent the three options when the "gene" is mutated. The path selection from point E may reach points F, G, and H, and if someone will pass through point F, he will pass through areas susceptible to epidemic infection. When the susceptible area is blocked, the path can only move to the upper left or lower right corner, as shown in Fig. B and Fig. C. The situation that the pathway is susceptible to epidemic infection in Fig. A is avoided. If the part of the ACO fails to avoid the situation in the areas susceptible to COVID-19, the part of the GA can avoid its path in time, and more effectively achieve the goal of the algorithm to achieve path avoidance.

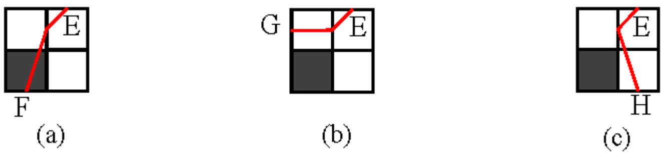


Fig. 5. Example of three cases of "gene" mutation

Table 2. The pseudo-code of the ACO part considering the impact of COVID-19 infection

Algorithm 2. ACO part considering the impact of COVID-19 infection
1: Q=λ % Q indicates the pheromone increase intensity coefficient; λ is a constant.
2: if in an area vulnerable to COVID-19 infection
3: Rho=m; %Rho indicates the pheromone volatility coefficient.
4: elseif in an area less susceptible to COVID-19 infection
5: Rho=n; %m and n are constants, and m>n.
6: end
7: delta_Tau=Q/L; %L indicates the length of the path taken by the ants in this cycle.
8: Tau=(1-Rho).*Tau+delta_Tau; %Tau represents a pheromone matrix.
%delta_Tau indicates pheromone increment.

5 Experiments and Analysis

5.1 Experimental Environment

The hardware environment of all experiments in this paper is the processor Intel(R) Core(TM) i5-6200U 2.30GHz, the memory is 4GB, and the hard disk is 465GB. The data preprocessing is completed in ArcGIS10.7 environment, and the simulation modeling part is carried out under the condition that the environment is MATLAB R2021a.

5.2 Acquisition, Selection and Processing of Data

Acquisition and Selection of Data. The researchers obtained the map of Taigu County from the GRIP dataset, Baidu satellite map and OpenStreetMap. Through comparison, it is found that some roads in Taigu County map in the GRIP dataset are missing, and the street information is incomplete, as shown in Fig. 6(a). The map from Baidu Satellite Map has some streets that are not clear and cannot display road and location information in layers, as shown in Fig. 6(b). The map of Taigu County from the GRIP dataset can not only display information such as roads, locations, and rivers in layers, but also specifically label road information, and the street information is also clear, as shown in Fig. 6(c). Therefore, the Taigu County map from OpenStreetMap is chosen as the data source for the study.

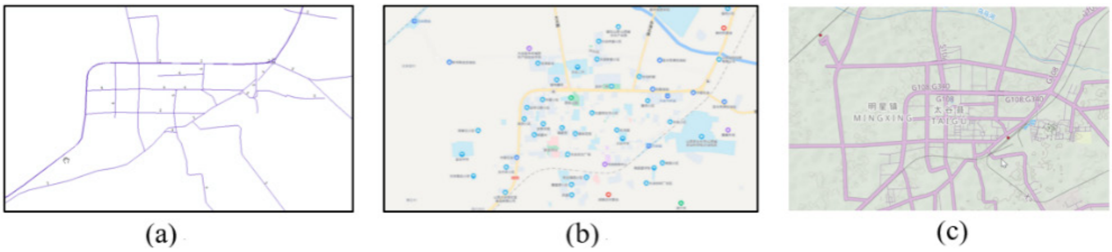


Fig. 6. Taigu county maps from different sources

Processing of Data. Fig. 6(a) is selected from Fig. 6 as input data. The input data is divided into 7 layers using ArcGIS software. According to the research needs, the data of the three layers of points, places and roads are selected to be retained, and the data of other layers are deleted, as shown in Fig. 7(a). The layers are then labeled and organized, as shown in Fig. 7(b). Label road information in the roads layer. Label important locations on the points layer, such as train stations, schools, hospitals, etc. In the Places layer, the medium and high risk areas where the COVID-19 occurred are marked. Then it is rasterized to generate the raster image, as shown in Fig. 7(c). The grid image is then binarized to form a binary image, as shown in Fig. 7(d). Fig. 7(d) is cropped and inverted to obtain Fig. 7(e), and its image information is converted into a digital matrix containing only 0 and 1.

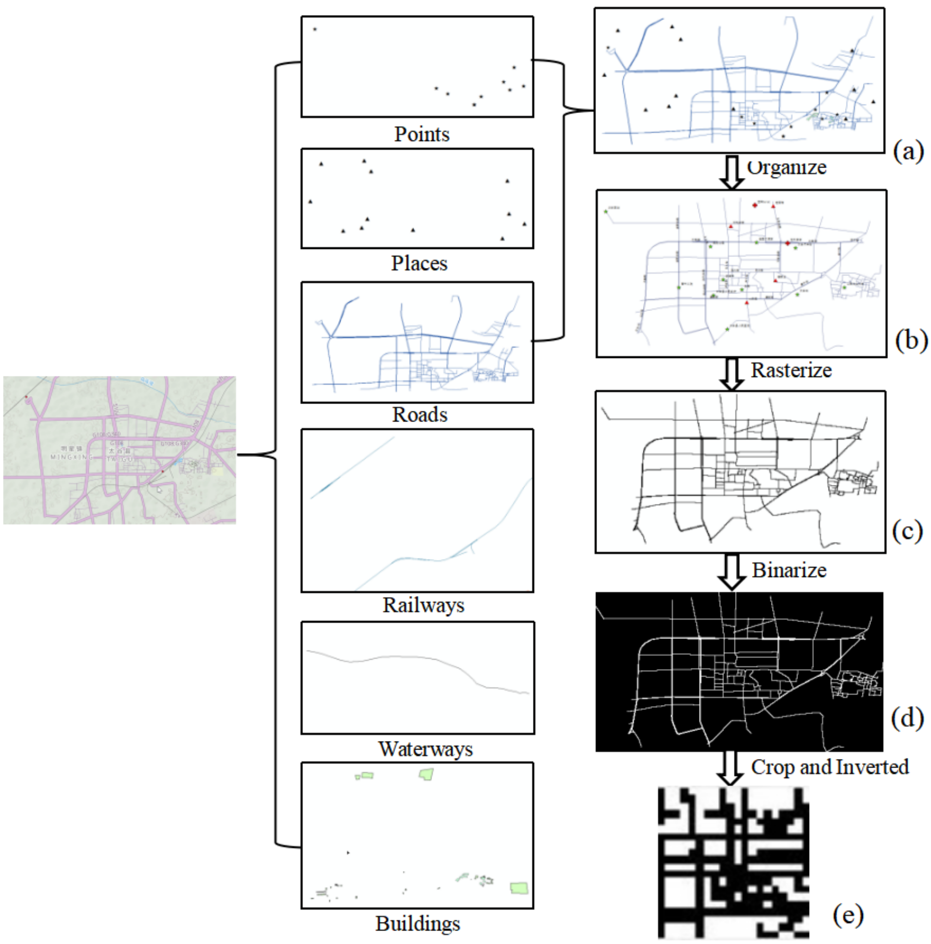


Fig. 7. Process diagram of data processing

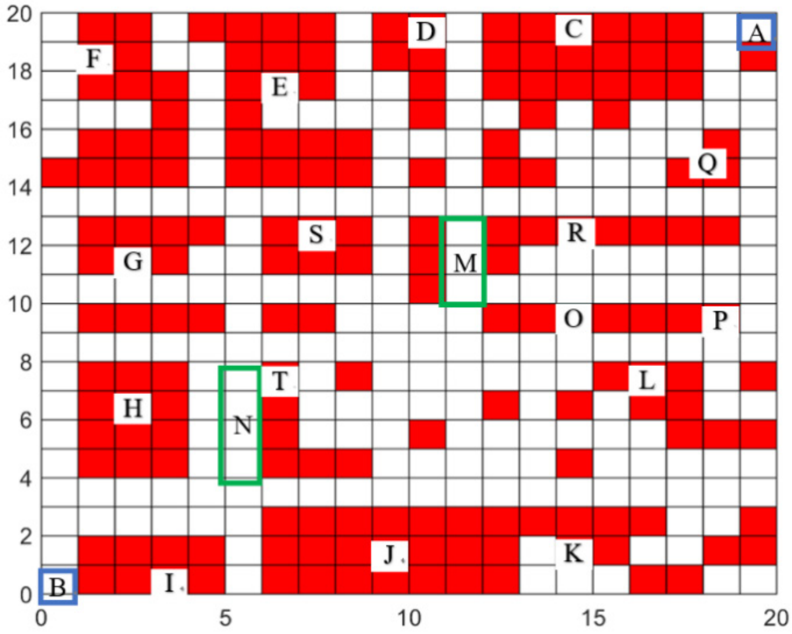


Fig. 8. Raster map

The 20x20 grid map drawn by the 0 and 1 matrix is shown in Fig. 8, which constitutes the grid map required for the experiment. The regions corresponding to the serial numbers A to T in the figure are shown in Table 3. Point A represents the starting point of the journey, and point B represents the ending point of the journey. Areas M and N represent areas susceptible to the COVID-19. The experiment planned the route from Xinlong Hotel to Culture Square in Taigu County, passing through places such as Middle School and Baoyuanlong Site.

Table 3. Location list

Letter	Name	Letter	Name	Letter	Name	Letter	Name
A	Xinlong Hotel	B	Culture Square	C	Jingu Square	D	Yiyuan Hotel
E	Technical School	F	Xiyuan Park	G	Housing Estate	H	Housing Estate
I	Taigu Government	J	Jinzhong College	K	Jewelry Store	L	Grocery store
M	South Street	N	Xidao Street	O	Drum Tower	P	Hospital
Q	Middle School	R	Housing Estate	S	Primary School	T	Baoyuanlong Site

5.3 Experimental Parameters and Analysis

The experimental algorithm adopts a hybrid algorithm combining ACO and GA. The experimental parameters include the number of ants, the parameters of relative weight of pheromone, heuristic information, pheromone evaporation coefficient, heuristic factor and pheromone increase intensity coefficient in the ACO. It also contains crossover probability, mutation probability, population size, and evolutionary generation representing GAs. The specific experimental parameter values are shown in Table 4.

Table 4. Experimental parameter values

Parameter	Value	Parameter	Value
The number of ants (m)	50	The maximum number of iterations (max)	100
Pheromone importance (Alpha)	2	Heuristic factor importance (Beta)	6
Pheromone evaporation coefficient (Rho)	0.3	Evolutionary generation (generation)	200
Crossover probability (Pc)	0.2	Mutation probability (Pm)	0.05

The updating of the pheromone matrix in the experiment affects the overall behavior of the ant colony. The GA can update the ant colony individuals in a single iteration through crossover and mutation operations. The hybrid algorithm adopts the principle of the whole and then the local to test and analyze the path between the starting point and the end point of the experiment.

5.4 Comparative Experiment and Analysis

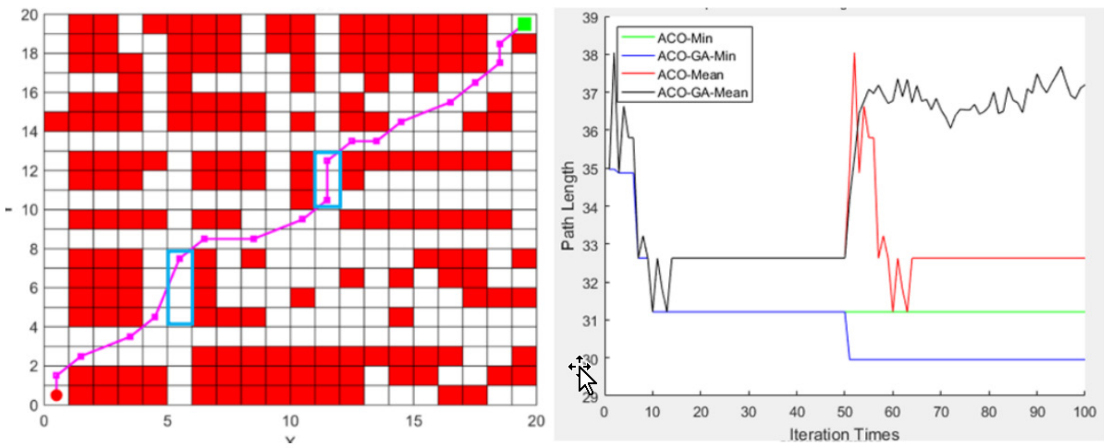
Experimental comparison mainly includes the following situations:

1) All points in the grid map have the same probability of being selected without considering the epidemic. An ACO-GA is used to select the path from the starting point to the ending point. The minimum path length is taken as the only measurement criterion, and the path selection is shown in Fig. 9(a). The path trajectory does not avoid the areas vulnerable to the epidemic. As shown in Fig. 9(b), the optimization curve of the ACO and the ACO-GA for path planning is compared, which also includes the comparison of the mean value of the path length of each iteration during the execution of the algorithm. The first 50 iterations of the experiment are completed by ACO, and the last 50 iterations are continued by ACO and GA respectively. Where ACO-Min and ACO-GA-Min respectively represent the optimal value curves of ACO and ACO-GA, while ACO-Mean and ACO-GA-Mean respectively represent the mean change of path length of each iteration of ACO and ACO-GA.

2) All points in the grid map have different probabilities of being selected when considering the epidemic. The M and N regions represent areas that are susceptible to epidemics, and the other grids represent areas that are not susceptible to epidemics. Other regions are easier to be selected than M and N regions to achieve the effect of epidemic protection. Changing pheromone volatilization intensity in the ACO can achieve the effect of path avoidance. As shown in Fig. 10(a), the path planning trajectory avoids M region and half avoids N region. In the other case, the planned trajectory of the path in Fig. 10(c) avoids both the M region and the N region. Fig. 10(b) and Fig. 10(d) represent the path optimization process in these two cases, respectively.

Analysis of the experimental results:

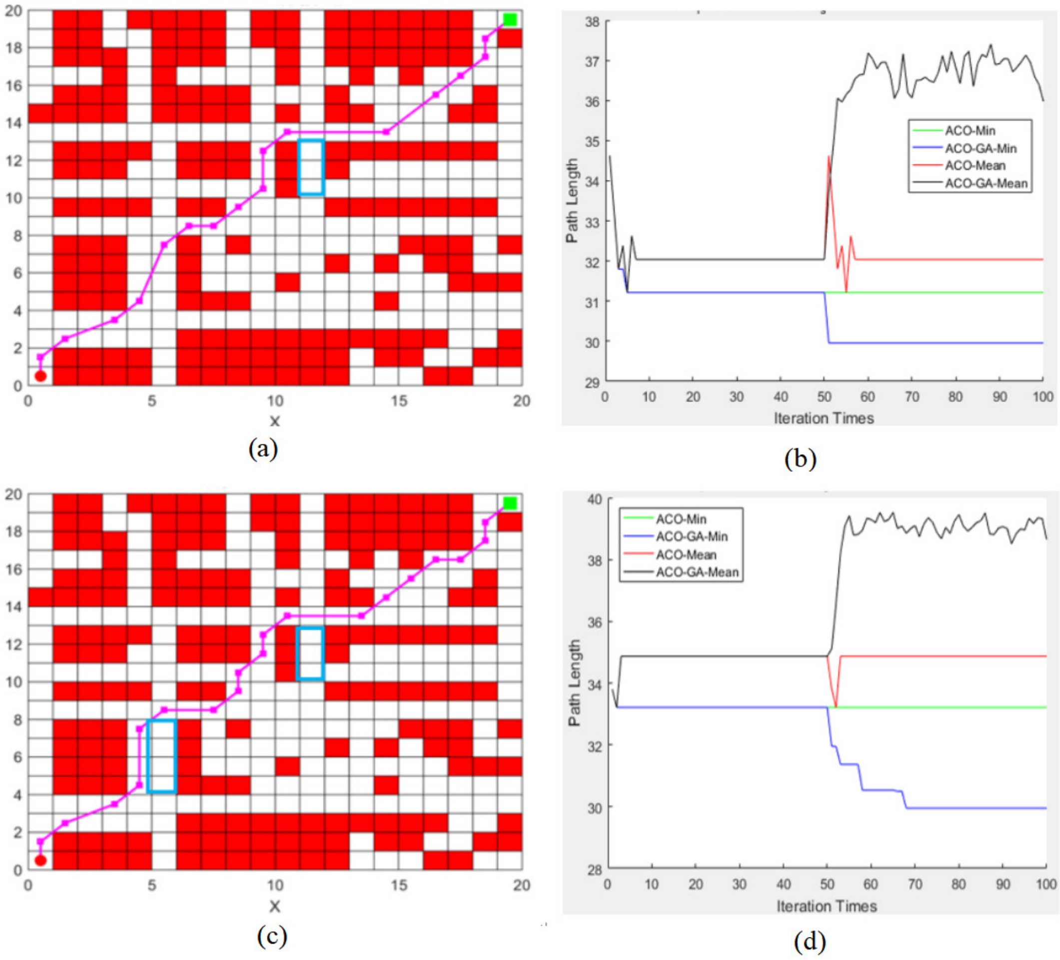
1) By comparing the curves in Fig. 9(b), it can be seen that the ACO has achieved a good effect after more than 10 searches due to its fast convergence speed in the early stage, and the subsequent ant colony search does not make better progress. After 50 iterations, the GA continues to converge efficiently to the optimal solution on the basis of the ACO results. This experiment shows that the GA can accelerate convergence in the later stage of path optimization. The ACO fell into the locally optimal value in the subsequent execution process, and the situation of not finding better search results is greatly improved. At the same time, this result has similar conclusions in Fig. 10(b) and Fig. 10(d).



(a) (b)

(a) Path trajectory diagram (b) Optimization curve diagram

Fig. 9. Experiments without considering the impact of COVID-19 infection



(a) Path trajectory diagram (past point M) (b) Optimization curve diagram (past point M)
(c) Path trajectory diagram (pass M and N points) (d) Optimization curve diagram (pass M and N points)

Fig. 10. Experiments that took into account the effects of COVID-19 infection

2) Compare the path optimization process in Fig. 9(b) and Fig. 10(b). In the searching process of the ACO in Fig. 10(b), the locally optimal result can be reached faster than that in Fig. 9(b), which is almost half of the iteration times. Similarly, a similar phenomenon is found by comparing the results in Fig. 10(d), which indicates that the ACO worked more efficiently with the increase of the infected area. Therefore, the number of iterations can be reduced appropriately to improve the efficiency of the algorithm.

3) Comparing the searching part of the GA in Fig. 9(b) and Fig. 10(b), the mean value of the paths in Fig. 10(b) reaches a stable state earlier, indicating that the subsequent GA is relatively stable due to the more stable result of the ACO. Similarly, a similar conclusion can be found in Fig. 10(d).

According to the above analysis, the experimental conclusion can be drawn that the ACO-GA can effectively improve the late convergence of the ACO. In this process, the convergence speed of the algorithm will be further accelerated with the increase of the blocked area in view of the change of the epidemic path.

6 Conclusions

The ACO-GA is obtained by combining the ACO and the GA. The algorithm considers the impact of COVID-19, improves the pheromone of the ACO and genetic initial population, and realizes path avoidance based on the map matrix. It is verified by experiments that the algorithm has faster convergence speed and is not easy to fall into the local optimum through the strategy of the whole and then the local, and has robustness and scalability.

Considering the impact of COVID-19 infection on urban roads, this paper selects the travel route in the urban center of Taigu County based on the ACO-GA. The experimental results show that the hybrid algorithm can effectively avoid areas susceptible to COVID-19 infection, and traveling according to the predicted path can greatly reduce the risk of COVID-19 infection and achieve the effect of path avoidance.

The ACO-GA still has a large optimization space in the number of iterations. In future studies, it can be further optimized for specific road schemes, and the efficiency of the algorithm can be further improved.

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